Pol. J. Environ. Stud. Vol. XX, No. X (XXXX), 1-11
DOI: *10.15244/pjoes/195787* ONLINE PUBLICATION DATE: 2025-01-29

Original Research

Driving Eco-Digital Transformation: Exploring the Industrial and Digital Pathways to Boost Carbon Emission Efficiency

Tifeng Liu[1]*, Shouzhi Liu[2], Pomi Shahbaz[3]

[1]School of Public Administration, Hohai University, Nanjing, 211100, China
[2]School of Language, Culture and Media, Hefei University, Hefei, 230000, China
[3]Department of Economics, Division of Management and Administrative Science, University of Education Lahore, Pakistan

Received: 27 August 2024
Accepted: 10 November 2024

Abstract

Carbon emissions mainly cause environmental devastation, and they're continuously rising in the atmosphere. It is responsible for global warming, which causes severe climatic events, including high temperatures and uneven rain distribution. However, the increasing global population has generated a high demand for sustainable energy production and consumption. Therefore, for sustainable economic development, it is necessary to produce economic outputs with minimal environmental hazards. This study measures the total factor carbon emissions (CEE), consisting of input and two types of output (gross domestic output as the desired output and CO_2 emissions as the undesired output), by utilizing complete data from 181 different economies for the period 1995-2022. Subsequently, it explores the dynamic relationship between the digital economy (DIGI), industrial structure (INDSI), population density (PD), and carbon emissions through the lens of the environmental Kuznets curve (EKC). Four econometric approaches were used to obtain robust findings to address the problems of heterogeneity, autocorrelation, and endogeneity. The outcomes revealed a significant positive impact of DIGI and INDSI and a negative impact of PD on carbon emissions. Moreover, INDSI significantly moderates the relationship between DIGI and CEE, increasing the positive environmental externality of DIGI. The findings also confirm the existence of the EKC, implying that CEE decreases with an increase in economic growth. After a certain level of economic growth, the CEE also started to increase. Therefore, both the DIGI and INDSI can significantly contribute to reducing carbon emissions, leading to a high CEE. Economies may adopt the incentive and award system, promote R&D in the industrial sector through the collaboration of academic and research institutions, and transform their structure along with the adoption of digital technologies to achieve the efficient use of energy and resources.

Keywords: environmental sustainability, climate change, carbon emissions, environmental hazards, digitalization

*e-mail: tliu942020@126.com

Introduction

Climate change-related destruction is not stopping, even though economic activity has slowed because of COVID-19. Greenhouse gases (GHGs) pollute the environment and cause global warming, as 95% of pollution emissions are because of GHGs. Among the GHGs, CO_2 is primarily responsible for accelerating climate change. CO_2 accounts for 79% of the GHG volume and has the longest atmospheric lifespan [1]. Moreover, CO_2 emissions have not yet been controlled, impeding the efforts of economies to maintain a balance between economic development and the environment. The increasing volume of carbon in the atmosphere leads to an increase in global temperature, causing serious challenges for humans on Earth, such as severe climate events, low food and water availability, and a high probability of diseases. These economic growth and environmental implications demand the reconsideration of emission reduction from the perspective of various socioeconomic aspects that affect emission levels. This implies that economies must find effective ways to reduce their carbon emissions along with low energy consumption to achieve green economic growth [2].

The 17 Sustainable Development Goals (SDGs) primarily focus on prosperity and well-being and require significant action in all spheres of life, along with the application of technological innovations. Achieving the UN SDGs is not possible without the three important aspects of an economy, namely industry, innovation, and infrastructure, emphasized in SDG-9. Technological advancements and structural adjustments are crucial for achieving this dual-carbon goal. Similarly, the Paris Agreement on Sustainable Development endorses the crucial role of cutting-edge technologies in achieving a sustainable future. Improvements in the industrial structure and adoption of innovations might contribute to the reduction in carbon emissions and energy conservation [3], which can play a significant role in improving carbon emission efficiency. Therefore, innovations can create a balance between economic growth and the environment. However, in the early stages of economic growth, it is difficult to maintain environmental sustainability and create a trade-off between economic growth and the environment [4]. This implies that basic human needs are highly prioritized over the environment in the early stages of development, and later on, with an increase in economic development, economies have started to adopt advanced and energy-efficient technologies to improve carbon emission efficiency.

The implementation of low-carbon transitions in resource-intensive industries is a major challenge to rapid economic growth. The industrial structure is highly dependent on the resources available in the region. Where the industry extensively uses these resources, it develops a compatible industry structure that directs the implementation of low-carbon transition in the region and also has an impact on carbon emission efficiency [5]. The traditional industry structure majorly contributes to carbon emissions, which are no longer effective for achieving low-carbon economic development. This needs to effectively transform the industrial structure, leading to low carbon emissions [6]. In the production process, the industry structure highly emits CO_2 because the carbon emission intensity and characteristics of CO_2 emissions differ among regions due to the different industrial structures. Therefore, the improvements and rationalization of the industrial structure directly affect carbon emission efficiency [5].

Considering carbon emission efficiency, the digital economy (DIGI) is a crucial aspect of an economy that is progressively effective in transforming economic structures, restructuring economic factors, and changing the competitive environment. The DIGI provides long-term benefits to the economy and has environmental implications. Considering its direct impact on carbon emission efficiency (CEE), there is still a lack of comprehensive literature that emphasizes global panel data; however, Lyu et al. [7] considered only a single country, which makes it difficult to generalize their findings in the global context. However, the DIGI and its impact on CO_2 emissions have been extensively analyzed. Most of them were also focused on the local domestic level, as is depicted in [8-10]. Yi et al. [9] analyzed the spatial spillover effect of DIGI on carbon emissions and found the direct and indirect reduction impact of DIGI on carbon emissions. Li and Wang [10] in China have found a U-shaped relationship between the DIGI and carbon emissions, which implies that DIGI first increases and then lowers carbon emissions. They also found a U-shaped spatial spillover impact of the DIGI on China's carbon emissions. Wang et al. [8] also used the entropy method to measure the DIGI index for China and found a significant negative impact of DIGI on carbon emissions in the country. Dong et al. [11] considered the panel of 60 different economies and found the declining impact of DIGI on carbon emission intensity but an increasing effect on per capita emissions.

The rapid expansion of DIGI worldwide has opened a new era of economic development by which economies have extensively focused on science and technology to cope with economic challenges and transform the global landscape after the pandemic. Digital infrastructure and digital industry chain restructuring are crucial aspects of the global digital economy that accelerate sustainable development [11]. Moreover, considering the role of DIGI in economies, it has extensively improved social digitalization, intelligence, and networking. The improvements seen with DIGI have occurred through digital industrialization and industrial digitization. The former explains the development of new digital industries, whereas industrial digitization refers to the transformation of traditional industries through the adoption of digital technologies. Therefore, DIGI fosters high-tech economic development along with the high adoption of innovations across different economic sectors. Similarly, the DIGI economy also has a favorable impact on the environment by lowering carbon emissions and increasing resource use efficiency in the industrial sector of the economy. Thus, there is still an extensive gap in research that clearly demonstrates the impact of industrial structure and DIGI on CEE at the global level. Considering this gap, this study contributes to the literature in several ways. First, the study comprehensively measures three different indices, namely the carbon emission efficiency index (CEEI), the digital economy index (DIGI), and the industrial structure index (INDSI), using the entropy method. Moreover, the study considers 181 different economies with complete data from 1995-2022 as the research period. Additionally, the study examines the direct impact of INDSI and DIGI on CEEI and finds that if this impact exists, then INDSI moderates the impact of DIGI on CEEI at the global level.

Review of Literature

Two factors can measure carbon emission efficiency (CEEI), such as "single factor (SF)" or total factor (TF)" CEEI. SF-SEEI is easy to measure and directly indicates environmental efficiency. For example, SF-CEEI is measured as carbon productivity, which is equal to the ratio of GDP in a year to gross CO_2 emissions, CO_2 emissions per unit of energy consumed, or a carbon index, CO_2 per capita divided by GDP, carbon intensity, and energy intensity [12-16]. All these SF-CEEIs have major limitations in the indicators considered in the measurement that do not broadly describe the CEEI because the CEEI is a multi-dimensional concept and depends on the complex functional form of environmental, economic, and social factors. SF-CEEI ignores the effects of inputs, such as labor, capital, and energy, and only considers outputs, such as GDP and CO_2 emissions [17]. The theory of total-factor productivity signifies that the TF-CEEI considers CO_2 along with the effects of different inputs and their substitutes on the CEEI [18]. Therefore, the TF-CEEI considers the input-output factors of a production process. These include labor, capital, energy consumption (as input factors), and desired and undesired outputs, resulting in a more comprehensive and reliable estimation of the CEEI. The current study also focuses on the TF-CEEI. In addition to the measurement, a wide range of studies have described the effects of various factors on regional CEEI. These include foreign direct investment [19], technological progress [2], market forces [20], industrial structure [5], urbanization [21], environmental regulation [22], and innovation [23].

INDSI is considered a crucial factor affecting CO_2 emissions and has been extensively studied by the academic community worldwide. Researchers have frequently examined CO_2 emissions and their influencing factors in light of the environmental Kuznets curve (EKC), the STIRPAT model, and the KAYA equation. [24]. Dong et al. [25] have analyzed the impact of industrial structure through the EKC hypothesis. They found that the improvement in industrial structure directly affects CO_2 emissions and influences global carbon emissions through the adoption of advanced and efficient technologies. Moreover, considering the STIRPAT model, Zhao and Xi [26] found a nonlinear impact of INDSI on carbon emissions. Han et al. [27] developed the KAYA equation and the LMDI decomposition method. They also found a negative impact of the INDSI on carbon emissions and energy consumption. Few studies have analyzed the mediating role of INDSI in the impact of energy structure on carbon emissions. Gao et al. [28] demonstrate the favorable role of upgrading industrial structures in the impact of green technologies on reducing carbon emissions.

CO_2 emissions are highly interlinked with the ecological environment and science and technology innovation industry. The rising level of carbon in the atmosphere creates severe disruptions such as a rise in sea level, diversity losses, and disequilibrium in ecology. On the other hand, innovation and technology play their role in mitigating the impact of these challenges by providing sustainable solutions in order to accelerate sustainable economic development [29, 30]. These technologies and innovations have a dual impact on carbon emissions. On the one hand, these technologies and innovations lower carbon emissions, owing to efficiency gains in energy consumption, cost savings, and different spillover effects of innovations and technologies [31]. Similarly, the DIGI not only contributes to rapid economic growth but also significantly improves environmental performance. DIGI also influences carbon emissions through the transformation of traditional environmental monitoring models. The digital economy fosters the upgrading of industrial systems by combining different computers and sensor systems, which develop a network for collecting information, facilitating data collection, transmitting information, accelerating management, lowering monitoring costs, and providing real-time data about the environment [32]. Therefore, DIGI provides information about resource deployment, lowers the chance of error in collected data, and provides data to develop effective environmental regulations to improve pollution management [33]. Additionally, DIGI also reduces the adverse effects of information asymmetry [34] and develops a strong competitive mechanism, forcing firms to invest more to lower their emission levels by achieving efficient use of their resources [35]. Moreover, DIGI brings about changes in connectivity and communication, which foster access to instantly shared information through the Internet. This provides an effective mechanism for traditional industries to upgrade their structure by adopting digital technologies and innovations to develop an intelligent and eco-friendly industry with low energy consumption carbon emissions [36, 37]. Energy is a major industry resource, and DIGI, in terms of digital devices, facilitates the industry's efficient use of energy. For example, the oil and gas industry has substantially improved its operational efficiency owing to the adoption of digital technologies [38]. By integrating digitalization into traditional energy companies, they significantly improve their energy production and consumption systems, energy mix, and environmental performance [39]. The rapid integration of digital technologies has led the industrial structure to transform from a resource-driven to an innovatively driven mode. Digital technologies also facilitate resource sharing among industries, which can optimize the production methods of the traditional industry [7, 40]. Therefore, it is clear that DIGI and INDSI have a strong impact on carbon emissions, and based on the arguments in the literature, it is clear that both variables may also have a strong impact on CEEI. Moreover, it also realized that the regional differences in industrial structures may also create the influential differences between DIGI and CEEI. Therefore, INDSI differences may amplify or diminish the effectiveness of DIGI on CEEI. Thus, the following hypothesis was developed:

H1: DIGI has a significant positive impact on CEEI.

H2: INDSI may have a significant impact on CEEI.

H3: INDSI may significantly moderate the impact of DIGI on CEEI.

Methodology

The outcomes of the current study are based on a panel of 173 different economies for the period 1995-2021. In the current study, CEEI was the dependent variable, measured according to the super-efficient SBM model developed by Tone [41]. This model includes inputs such as labor (L), capital stock (K), total energy consumption (direct and indirect energy), and two outputs: GDP (desired output) and CO_2 emissions (undesired output). Table 1 presents the descriptions and sources of the variables used in the measurement of the CEEI. Labor inputs indicate the total number of laborers in the industry sector of the economy at the end of each year. For capital stock, we use gross fixed capital formation because it represents the long-term physical assets that play a crucial role in enhancing the productive capacity of an economy. This involves machinery, equipment, and infrastructure that directly affect industrial activities. The energy consumption includes both direct and indirect energy consumption. Direct energy consists of oil, coal, and natural gas, whereas direct energy consists of renewable energy and electricity. All this energy data is openly available at https://www.eia.gov/. All data on labor, capital, GDP, and CO_2 emissions are also openly available at https://databank.worldbank.org/source/world-development-indicators.

DIGI was the first core independent variable in this study. DIGI is a precise determinant of the digital economy and consists of various indicators. Table 2 presents a description of the indicators used to measure DIGI, which is expected to be representative of the digital economy. A total of seven indicators were included in the DIGI measurement, and these indicators also consisted of further sub-indicators. The data are available from the World Development Indicators Database (https://databank.worldbank.org/source/world-development-indicators) for all sub-indicators. Using the entropy method, the weights for each sub-indicator were calculated to obtain the DIGI.

The third core independent variable is industrial structure (INDSI), which is also measured using the different indicators (Table 3). This index was measured using the entropy method.

Along with DIGI and INDSI, this study also includes GDP and GDP squared to confirm the EKC hypothesis in terms of CEEI. Population density, which is also a crucial factor affecting CEEI, was included as an independent variable. Therefore, the functional form is developed in Eq. (1), which includes CEEI as the dependent variable and GDP, GDP squared, DIGI, INDSI, and population density (PD) as independent variables.

$$CEEI = f(GDP, GDP^2, DIGI, INDSI, PD) \quad (1)$$

Where GDP and GDP2 are included in the model to examine the EKC hypothesis, DIGI is the digital economy index, INDSI is the industrial structure, and PD is population density. Subsequently, the following econometric model is specified:

Table 1. Input and output information for measuring CEEI.

Inputs	Description	Units	Source
Labor	Total labor employment in the industry	Numbers	WDI
Capital	Gross fixed capital formation	Current US$	WDI
Energy	Direct and indirect energy consumption	Mega joule	EIA
Output			
GDP	Gross domestic product	Current US$	WDI
CO_2 emission	Carbon emission	Kt	WDI

Table 2. Indicators used for measuring the DIGI.

Indicators	Sub-Indicators	Description	Units	Source
Digital Access and Connectivity	Mobile cellular subscriptions	Subscriptions to a public mobile telephone service providing access to the PSTN using cellular technology	Per 100 peoples	WDI
	Fixed broadband subscriptions	Subscriptions to high-speed public internet	Per 100 peoples	WDI
	Internet users	Individuals who have used the internet in the last three months	% of population	WDI
	Fixed telephone subscriptions	Active number of fixed lines	Per 100 peoples	
Secure internet	Secure internet server	Number of distinct publicly trusted TLS/SSL certificates	Per 1 million peoples	WDI
ICT trade	ICT goods export	Information and communication technology goods export	% of commercial goods export	WDI
	ICT goods import	Information and communication technology goods import	% of commercial goods import	WDI
	ICT services export	Information and communication technology services export	% of commercial services export	WDI
	ICT services import	Information and communication technology services export	% of commercial services export	WDI
High-tech and innovation	High-technology exports	Products with high R&D intensity		WDI
	Patent applications			WDI
	R& D expenditures	Expenditures on R & D	% of GDP	WDI
Financial inclusion	Account ownership at a financial institution or with a mobile-money-service provider	Respondents having an account at a bank or other financial institutions	% of the population of 15 plus	WDI
Education and Human capital	School enrollment	Tertiary education school enrollment	% Gross enrollment	WDI
	Literacy rate	Literacy rate in adult	% of people ages 15 and above	WDI
ICT investment	Investment in ICT with private participation	Investment in ICT projects with private participation	Current US$	WDI
	Public-private partnerships investment in ICT		Current US$	WDI

$$CEEI_{it} = \beta_0 + \beta Z_{it} + \delta_i + \rho_t + e_{it} \tag{2}$$

Where Z is a vector of independent variables mentioned in Eq. (1), i indicates the country, and t shows time. β indicates the undermined coefficients, δ_i captures the fixed effect, ρ_t signifies the random effect, and e_{it} is error term. We have applied different econometric approaches to measure the parameters mentioned above, such as fixed effect (FE), random effect (RE), and cross-sectional feasible generalized least squares (CS-FGLS). FE treats δ_i and ρ_t as part of the regression parameters, while RE considers them as part of the error term [42]. The model in Eq. (2) is further decomposed into M-1, M-2, and M-3. M-1 includes only DIGI along with GDP, GDP^2, and PD; M-2 includes only INDSI, while M-3 includes both DIGI and INDSI, along with their interaction term, to analyze the moderating effect of INDSI on the relations of DIGI with CEEI.

$$CEEI = \beta_o + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \beta_3 DIGI_{it} + \beta_4 PD_{it} + e_{it} \qquad \text{M-1}$$

$$CEEI = \beta_o + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \beta_5 INDSI_{it} + \beta_4 PD_{it} + e_{it} \qquad \text{M-2}$$

$$CEEI = \beta_o + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \beta_3 DIGI_{it} + \beta_5 INDSI_{it} + \beta_4 PD_{it} + \beta_6 DIGI_{it} * INDSI_{it} + e_{it} \qquad \text{M-3}$$

After the estimation of the above equations, M-3 can be used to measure the elasticities of CEEI regarding DIGI in order to explore the favorable contribution of the moderator (INDSI) in the influence of DIGI on CEEI. As INDSI scores fluctuate from 0 to 1, and considering these values of INDSI, we can check the impact of INDSI as a moderator between DIGI and CEEI.

Table 3. Indicators used for measuring INDSI.

Indicators	Description	Units	Source
Industrial sector contribution	Industrial sector share in GDP, indicating the size and importance of the industry	% of GDP	WDI
Manufacturing contribution	Specific contribution of the manufacturing sector within the broader industry	% of GDP	WDI
Trade dimension	Export and import of goods and services	% of GDP	WDI

$$\frac{\partial CEEI_{i,t}}{\partial DIGI_{i,t}} = \{M-3 : \beta_3 + \beta_6 INDSI_{it}$$

The heterogeneity issue, because of the specific characteristics of different economies, may provide biased estimates measured by FE and RE. Additionally, FE and RF are not reliable estimators in the presence of serial correlation and endogeneity issues [43]. For example, PD may lower the CEEI in the presence of endogeneity. To tackle the heteroskedasticity, we first used the logarithmic approach to transform the variables and then applied CS-FGLS. Additionally, system GMM is applied to eliminate biases due to the possibility of an endogeneity issue. System GMM is a very effective approach to get reliable estimates in the presence of mitigation bias, heterogeneity, variable omission, and endogeneity [44, 45]. Additionally, system-GMM effectively tackles autocorrelation and heteroskedasticity and provides consistent and reliable estimates when independent variables are not exogenous [46, 47]. The Sargan test of overidentification and the Arellano-Bond (AR2) test of serial autocorrelation ensure the consistency of the system-GMM. Moreover, T<N also endorses the application of system-GMM, and Eq. (3) is developed.

$$CEEI_{it} = \beta_0 + \alpha\, CEEI_{it-1} + \beta\, Z_{it} + \delta_i + \varepsilon_{it} \quad (3)$$

Where $\varepsilon_{it} = \rho_t + \epsilon_{it}$

Eq. (3) contains the 1st difference of CEEI, which yields:

$$\Delta CEEI_{it} = \alpha\, \Delta CEEI_{it-1} + \beta\, \Delta Z_{it} + \Delta\varepsilon_{it} \quad (4)$$

Where Δ is the difference operator; it eliminates the FE of countries. Therefore, system-GMM provides robust evidence for the outcomes of FE, RE, and FGLS models.

Results

Table 4 presents the mean values of the variables under consideration. The estimated index value of the CEEI was 0.725. This implies that economies are moderately efficient in lowering carbon emissions over the period–1995-2021. The minimum (0.377) and maximum (0.967) values of the CEEI indicate a high range of data, which demonstrates that some economies in the panel are efficient. The average value of DIGI is 0.100, which emphasizes that economies generally do not have a good level of digitalization. However, the maximum value (0.418) indicates that some economies may have a moderate level of digitalization. The INDSI score (0.207) also exhibits a low level of industrial structure in the economies over the period of 1995-2021. Although the minimum INDSI is 0.001, indicating the lowest level of industrialization, the maximum INDSI score of 0.813 depicts economies with heavily industrialized structures. The average value of lnGDP is 9.409, with a standard deviation of 1.164, indicating substantial differences among the sizes of the economies. The average lnPD score indicates a moderate level of population density across the dataset, while the minimum (0.409) and maximum (9.980) scores show that some economies are lightly populated and others are densely populated.

Table 5 lists the correlation matrices. DIGI was significantly correlated with CEEI, with a score of 0.060, indicating a positive correlation between DIGI and CEEI. INDSI, lnGDP, and lnPD are significantly and negatively correlated with CEEI at the 1% level of significance.

Table 6 shows the findings of three different econometric methods: FE, RE, and cross-sectional FGLS. All models provided robust empirical estimates, according to expectations. The coefficient sign and

Table 4. Descriptive analysis of variables.

Variables	Mean	Std. Dev.	Min	Max
CEEI	0.725	0.082	0.377	0.967
DIGI	0.100	0.062	0.0001	0.418
INDSI	0.207	0.088	0.0001	0.813
lnGDP	9.409	1.164	6.287	12.066
lnPD	4.266	1.502	0.409	9.980

Table 5. Correlation matrix.

Variables	CEEI	DIGI	INDSI	lnGDP	lnPD
CEEI	1.000				
DIGI	0.060*	1.000			
INDSI	-0.114*	0.019	1.000		
lnGDP	-0.208*	0.139*	0.191*	1.000	
lnPD	-0.106*	-0.018	0.111*	0.129*	1.000

*Shows significance level at 1%.

magnitude of lnGDP and lnGDP2 confirm the existence of the EKC hypothesis with the CEEI. The negative sign of lnGDP and the positive sign of lnGDP2 demonstrate that a rise in economic growth decreases CEEI, and after reaching a certain level of economic growth, economic growth increases CEEI. The individual impact of DIGI on CEEI is significant and positive. The magnitude of the impact resulting from all three models ranged from 0.0127 to 0.047. A coefficient value of 0.012 implies that an increase in digitalization in the economy increases the efficiency of carbon emissions. INDSI has a significant positive impact on CEEI, which implies that an increase in INDSI increases the efficiency of carbon emissions. lnPD indicates the significant negative impact of population density on the efficiency of economies' carbon emissions.

Robustness Check

The FE, RE, and CS-FGLS provide a significant impact on the variables, and it is important to test their robustness. For this purpose, the system-GMM is applied, and it provides robust evidence of the significant positive impact of DIGI and INDSI on CEEI in Table 7. Moreover, system GMM also indicates a significant positive moderating role of INDSI in the relationship between DIGI and CEEI. The Hansen test confirmed no model misspecifications. Additionally, the insignificant outcomes of the AR(2) test confirm no serial correlation in the errors.

Table 6. Findings of FE, RE and FGLS.

Variables	FE			RE			CS-FGLS		
	M-1	M-2	M-3	M-1	M-2	M-3	M-1	M-2	M-3
lnGDP	-0.227* (0.036)	-0.226* (0.036)	-0.227* (0.035)	-0.177* (0.029)	-0.176* (0.028)	-0.177* (0.029)	-0.132* (0.015)	-0.015* (0.001	-0.014* (0.003)
lnGDP2	0.011* (0.002)	0.011* (0.002)	0.011* (0.002)	0.008* (0.002)	0.008* (0.002)	0.008* (0.002)	0.007** (0.003)	0.009* (0.0003	0.0069** (0.003)
DIGI	0.0129* (0.001)		0.0127* (0.001)	0.0183** (0.007)		0.0181** (0.006)	0.047* (0.007)		0.025* (0.004)
INDSI		0.014* (0.003)	0.015* (0.0012)		0.019** (0.008)	0.02** (0.0079)		0.065* (0.013)	0.015** (0.006)
DIGI*INDSI			0.0145* (0.004)			0.016** (0.006)			0.807* (0.201)
lnPD	-0.025* (0.007)	-0.025* (0.007)	-0.025* (0.007)	-0.009* (0.003)	-0.009* (0.002)	-0.009* (0.002)	-0.004* (0.0007)	-0.003* (0.0006)	-0.005* (0.0005)
Constant	1.978* (0.158)	1.982* (0.156)	1.985* (0.158)	1.67* (0.132)	1.675* (0.132)	1.675* (0.132)	0.81* (0.071)	0.890* (12.28)	0.87* (0.072)
R^2	0.029	0.028	0.029	0.051	0.053	0.053			
F-test	34.77*	33.57*	23.72*						
Chi-square				132.27*	129.02*	136.87*	247.20*	264.26*	287.41*

FE = Fixed effect; R E= Random effect; CS-FGLS = Cross sectional feasible generalized least squares
M-1 = Model-1; M-2 = Model-2; M-3 = Model-3
** p<0.01, ** p<0.05, *** p<0.1*

Table 7. Robust test system-GMM.

Variables	System-GMM		
	M-1	M-2	M-3
L.CEEI	0.38* (0.006)	0.382* (0.006)	0.378* (0.008)
lnGDP	-0.134* (0.016)	-0.119* (0.016)	-0.129* (0.016)
lnGDP2	0.007* (0.001)	0.006* (0.001)	0.006* (0.001)
DIGI	0.0021* (0.0001)		0.0019* (0.0001)
INDSI		-0.019* (0.004)	-0.022* (0.004)
DIGI*INDSI			0.008* (0.0005)
lnPD	-0.001* (0.0003)	-0.001* (0.0003)	-0.001* (0.0003)
Constant	-1.061* (0.068)	1.982* (0.156)	1.08* (0.07)
F-test	520.89*	19.74*	94.87*
AR (2)	4.32	4.34	4.33
Sargan test	3.96	3.98	3.93
Hansen test	16.04	16.09	16.2

*Shows significance level at 1%.

Discussion

Carbon emissions are primarily responsible for environmental destruction worldwide because of their rising role in global warming. Lowering emission levels is one of the most important topics of debate among social and environmental scientists. As the CO_2 volume in the atmosphere increases, it traps heat and causes severe extreme weather events. The scientific consensus confirms that human activities, particularly increasing levels of energy consumption, industrial processes, and severe deforestation, have been the primary drivers of the exceptional rise in CO_2 in the atmosphere since the Industrial Revolution. This has accelerated the global debate on how to reduce carbon emissions to mitigate the impact of climate change. However, CEE is a more sustainable and comprehensive approach than considering only a reduction in carbon emissions. Lowering carbon emissions is important for mitigating the immediate impact of climate change; however, CEE provides a comprehensive approach that considers economic growth while reducing carbon emissions.

The current study aimed to analyze the dynamic relationship between variables such as DIGI, INDSI, and lnPD on CEEI in light of the EKC hypothesis. Moreover, this study explored the moderating role of INDSI in the relationship between DIGI and CEEI. Different econometric approaches have provided robust estimates based on a panel of 173 different economies over the period 1995–2021. The findings revealed a significant positive impact of DIGI on CEEI. These results are consistent with those reported by Lyu et al. [7]. The positive impact of DIGI on CEEI can be discussed through various mechanisms, such as technological innovation and structural improvements. DIGI fosters the adoption of advanced technologies to lower energy consumption, which results in reduced carbon intensity in industries. The impact of DIGI on CEEI is strong in regions with high integration of digital technologies in industries [48]. Moreover, the lowering impact of DIGI on carbon emissions is justifiable because the digital economy has developed a management system that effectively upgrades the consumption and energy structure, leading to low carbon emissions [49]. Digitalization is a crucial driver for stabilizing economic growth while lowering energy consumption [50] and upgrading the industrial production process [51]. Along with the advantages of IT, DIGI extensively lowers input costs, expands the production level and sales channels of firms, enhances output economic efficiency, and reduces unnecessary energy use [52]. Song et al. [53] demonstrate the U-shaped impact of DIGI on CEE and also describe the mediation impact of technological innovation on the relation of DIGI and CEE.

The positive impact of INDSI on CEE implies that the transformation of the industrial structure increases CEE. INDSI has a strong impact on CEE through the allocation of inputs and technological advancement.

The imbalance in labor and energy allocation within the industrial sector may adversely affect CEE. For example, the labor-intensive industrial sector suffers from inappropriate labor distribution, and energy-intensive sectors face the major challenge of imbalances in energy allocation [54]. Our findings are in line with those of [55]. They described that a change in industrial structure may result in low carbon emissions. They found that if linkages between the manufacturing and service sectors increased, carbon emissions per capita decreased. Moreover, industrial sector transformation and improvements are necessary for reducing CO_2 emissions in the atmosphere because they have a substantial favorable impact on enhancing total factor productivity, leading to low carbon emissions per unit of economic output [25]. Similarly, Feng et al. [56] endorse the favorable effects of optimizing industrial structure on the environment through the efficient reduction of carbon emissions along with high economic benefits and high employment.

Considering the moderating impact of INDSI, the findings reveal that it substantially increases the positive externalities of DIGI to enhance the efficiency of carbon emissions by economies. INDSI's moderating role in the relationship between DIGI and CEE is shaped by how digital technologies and innovations are integrated and adopted in various economic sectors. With the economies' industrial sector, which is highly dependent on heavy manufacturing, DIGI provides an effective network that streamlines the production process, lowers input waste, and improves the efficiency of energy consumption, leading to high CEE [48, 57]. Therefore, the industrial structure of an economy determines how effectively the DIGI plays a crucial role in lowering carbon emissions while improving factor productivity. Lyu et al. [7] state that industrial structure rationalization weakens the impact of DIGI on CEE while upgrading industrial structure enhances its impact on CEE. Therefore, the moderating effect of INDSI affects how DIGI influences CEE. The elements of industrial structure, such as market competition, property rights, and capital investment, moderate the impact of DIGI on carbon performance [58].

The findings of the study also confirm the EKC hypothesis, which implies that first, CEEI reduces as economic growth increases, and after a certain level of economic growth, CEEI improves with an increase in economic growth. This could be explained by the fact that, when the economy grows, it starts to expand its economic activities, demanding high input and energy, which leads to high carbon emissions. When a country continuously experiences high economic growth, it starts to adopt advanced and efficient technologies that lead to the efficient use of economic resources and energy, leading to lower carbon emissions and high total factor productivity. The significant and negative impact of PD on CEEI implies that high PD lowers CEEI because of an increase in energy consumption and use of resources. Densely populated economies are characterized by a high demand for resources, transportation, and energy. This causes high waste production and inefficient energy use, leading to high carbon emissions with similar output levels. Our results are in line with those of Rahman [59] and Mohsin et al. [60] in terms of the impact of population density on the environment.

Conclusion

The continuous rise in the world population, along with the high demand for food and other necessities, majorly threatens the environment. Using economic resources and energy and producing output at an equal pace with the increasing population attracts researchers to explore carbon emission efficiency (CEE) rather than focusing only on carbon emissions. CEE indicates the ability of an economy to produce economic output with minimal levels of carbon emissions. Therefore, the current study is planned to explore the individual impact of the digital economy (DIGI) and industrial structure (INDSI) along with population density (PD) in the light of the EKC hypothesis. This study used different econometric approaches, including FE, RE, CS-FGLS, and system-GMM, to obtain robust estimates based on a panel of 181 economies over the period 1995-2022. For this purpose, the current study used the super-efficient SBM model to measure the total factor CEE index. The DIGI and INDFSI were measured by calculating the weights through the application of the entropy method.

The findings confirm the existence of the EKC hypothesis, which implies that, at first, the CEE decreases with the increase in economic growth, and after a certain level of GDP, the CEE tends to increase with the increase in economic growth. Moreover, all econometric models provide robust evidence for the significant positive impact of DIGI and INDSI on CEE. This indicates that the rise in digitization in the economy and improvements in the industrial structure positively contribute to the efficiency of carbon emissions. Moreover, the significant positive impact of the interaction term (DIGI*INDSI) signifies the favorable moderating impact of INDSI on the relation between DIGI and CEE. The elasticity analysis confirms this moderation effect of INDSI by indicating that the positive externalities of DIGI on CEE are increased when the industrial structure is improved. The significant negative coefficient of PD on CEE describes that densely populated economies lower the CEE.

Based on the findings of the study, the following policy implications are proposed. The economies may adopt incentives such as taxes, grants, and subsidies to foster the adoption of digital technologies in the industrial sector in order to use resources and energy efficiently. Governments may launch an award system to encourage industries that are less energy-intensive and more aligned with digitization. Promoting R&D in the industrial sector with the collaboration of academic and research institutions must be encouraged by providing funds for mutual academic and industry projects to improve resource and energy consumption and lower carbon emissions.

Conflict of Interest

The authors declare no conflict of interest.

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